Multiple fault detection and isolation

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MULTIPLE FAULT DETECTION AND ISOLATION

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Abstract: Model-based fault detection methods allow the generation of residuals as fault indicators. Isolation is generally based on the incidence matrix structure. Simultaneous faults generate a new fault signature, corresponding to the superposition of the fault effects. With classical decision methods, each fault combination results in a new residual configuration, leading to an extra column in an extended incidence matrix. This solution is extremely combinatorial. This work uses the structural properties of the incidence matrix corresponding to single faults to reason about fault combinations. This reasoning is implemented as a fuzzy inference system to take uncertainties into account. An implementation of this algorithm has been applied to an automotive engine.

Keywords: diagnosis, fault detection, fault isolation, fuzzy-logic, decision making, automotive engine.

1. INTRODUCTION

Fault diagnosis is based on three fundamental functions described by Isermann and Ballé, (1997): fault detection; fault isolation; fault identification.
Model-based fault detection (MFD) methods allow the generation of residuals defined as fault indicators, based on a deviation between measurements and model-based computations. The basic MFD methods such as parity equations (Gertler 1997), or state and output observers (Patton and Chen, 1997), use analytical redundancy to achieve the fault isolation function. Classically M residuals r_i (i=1...M) are generated. When a fault F_j, (j=1...N) occurs, some residuals stay close to zero and others become clearly different from zero. The residual state is usually translated, using a threshold, into boolean terms 0 or 1 in the $D(M \times N)$ incidence matrix.

$$D(M\times N)=\begin{array}{cc} \begin{array}{ccccc} F_1 & \dots & F_j & \dots & F_N \end{array} & \\ \begin{bmatrix} 1 & \dots & 0 & \dots & 1 \\ 0 & \dots & 1 & \dots & \dots \\ 1 & \dots & 0 & \dots & \dots \\ 0 & \dots & \dots & \dots & \dots \\ 0 & \dots & 1 & \dots & 0 \end{bmatrix} & \begin{array}{c} r_1 \\ r_2 \\ r_i \\ . \\ r_M \end{array} \end{array} \qquad (1)$$

The purpose of isolation function is to find which fault F_j appears in the system. Column j of the incidence matrix represents the signature of fault F_j. The fault isolation capability depends on the incidence matrix structure (Gertler and Anderson, 1992).

Comparison between the boolean incidence matrix columns and the residual vector is not an elementary problem. Subsequently, this paper proposes to solve the problem as a decision making problem in an uncertain environment using fuzzy rules as:

IF residual 1 is different from zero
AND residual 2 is close to zero
AND ...
THEN the fault x occurrence is True. (2)

Moreover, in some systems, several faults may appear simultaneously. Usually this situation is encountered when the system has not been interrupted after the first fault occurrence, either because this fault is not critical or its effect is gradual, and meanwhile, a second fault appears. This situation is more frequent when a reconfiguration method is used. Reconfiguration methods adapt the control law, allowing the production to continue in spite of the fault occurrence.

The rules (2) are no more efficient for multiple fault isolation because the occurrence of two simultaneous faults in the system leads to a new fault signature (Koscielny, 1993), corresponding to the superposition of the two fault effects. Under the linearity hypothesis, isolation of multiple faults may be processed using an extended incidence matrix, including a new column for each fault combination, leading to a combinatorial solution. In the following, this problem is solved using an original decision method which does not require testing of each combination.

This paper is organised as follows: the first section describes residual fuzzification while the second section presents the decision module and the symptom aggregation by fuzzy reasoning. Then the method is illustrated by an application to an automotive engine.

2. FUZZIFICATION

The residuals are never really equal to zero (noise, model uncertainties). Hence, the concept of *zero* is vague. The residual sensitive to a fault is theoretically just defined as different from zero, but a residual is affected with different amplitudes depending on the fault amplitude and the residual sensitivity to the considered fault. Thus the concept of *one* in the incidence matrix is also vague. In the following, fuzzy sets are used in order to translate the concepts of "close to 0", and "different from 0".

2.1.Residual fuzzification.

In the following, the incidence matrix is assumed to be statistically isolable (Gertler, and Anderson, 1992). The residual vector is defined at each sampling period as :

$$C(k) = \begin{bmatrix} r_1(k) & \dots & r_i(k) & \dots & r_M(k) \end{bmatrix}^T . \quad (3)$$

The fuzzy partition related to each residual is assumed to be a normalised fuzzy partition composed by two numerical fuzzy sets:

- Non Zero (symbol *NZ*), the grade of membership of the residual r_i to this fuzzy sub-set translates the concept "different from 0". Thus this function increases when r_i is *significantly affected* by fault F_j and fault F_j occurs.
- Zero (symbol *Z*), the grade of membership of the residual r_i to this fuzzy sub-set translates the concept "close to 0"; thus this function increases when no fault occurs or when a fault F_j occurs but r_i is *not significantly affected* by this fault.

For the sake of simplicity, in this paper, the fuzzy partition is limited to two linguistic terms but additional terms like "Undetermined", "Small", etc. could also be introduced.

Based on the fuzzy meaning of the two terms *NZ* and *Z*, that is μ_{NZ} and μ_Z, a symbolic fuzzification of the residual r_i over the set {*Z*, *NZ*} can be obtained (Foulloy and Galichet, 1995). Using the additive notation for discrete fuzzy subsets:

$$\mathcal{D}(r_i) = \alpha_1/Z + \alpha_2/NZ \quad (4)$$

with $\alpha_1 = \mu_{(Z)}(r_i)$ and $\alpha_2 = \mu_{(NZ)}(r_i)$. The fuzzy subset $\mathcal{D}(r_i)$ can also be characterised by its membership function $\mu_{\mathcal{D}(ri)}$ and therefore $\mu_{\mathcal{D}(ri)}(Z) = \alpha_1$. Afterwards, for the sake of simplicity, $\mu_{ri}(Z)$ and $\mu_{ri}(NZ)$ instead of $\mu_{\mathcal{D}(ri)}(Z)$ and $\mu_{\mathcal{D}(ri)}(NZ)$ will be used.

2.2.Fault attribute definitions.

Fault F_j is associated with four attributes:

- *Occurrence*: which characterises the fault materialisation (Occ).
- *Simultaneity Hypothesis*: which characterises the hypothesis that another fault F_k ($k \neq j$) occurs (Sim-Hyp).
- *Simultaneous*: which characterises a fault occurring simultaneously with another one (Sim).
- *Single*: which characterises the fault uniqueness (Sig).

Each attribute is represented by a fuzzy subset defined on the set of two linguistic terms {*True*, *False*}.

3. DECISION STEPS

The system is assumed to behave such that the following hypothesis is considered: *The fault effects are approximately added and the new signature generated by multiple faults is given by an OR logical operator between the different single fault signatures.* The proposed method is divided into four steps as shown in figure 1 and is based on a reasoning carried out on each fault independently of the others, thus using the same incidence matrix as the single fault case.

- The first step computes the truth (veracity) of the Occurrence attribute for fault F_j, using a rule-set (Occurrence Rules) based on the knowledge related to the elements equal to **1** in the binary incidence matrix.
- The second step computes the truth of the simultaneity hypothesis for fault F_j, using a rule-set (Sim-hyp Rules) based on the knowledge related to the elements equal to **0** in the binary incidence matrix. At this stage, multiple faults is a hypothesis which needs to be further reinforced.
- The third step allows the separation between single faults and multiple faults by computing the *Sig* attribute and *Sim* attribute by aggregation of the results of the first and second steps.
- Then, the final decision presents the single or multiple faults which have occurred.

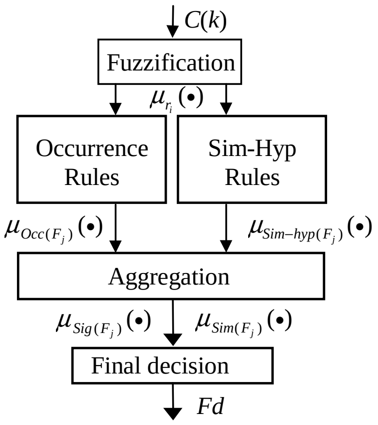

Fig. 1. Decision strategy.

3.1.Occurrence rules.

The *Occurrence* attribute characterises fault F_j and is represented by a fuzzy subset as shown in figure 2.

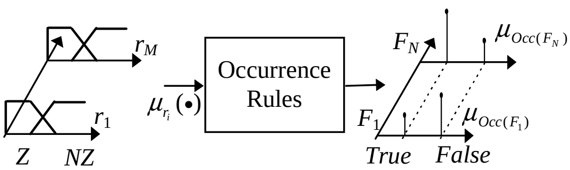

Fig. 2. Occurrence rules.

Since the occurrence of fault F_j should be *True*, if the fault affects the system behaviour, only elements equal to 1 in the signature are useful for the computation of the *Occ* attribute fuzzy subset. Thus, fault F_j occurs if the residual r_i belongs strongly to *NZ* when $D(i,j)$ is equal to 1.

Now if $D(i,j) = 0$, then r_i cannot bring any information about the occurrence of fault F_j, because the residual r_i might belong to the *NZ* fuzzy subset and another fault F_k (with $D(i,k) = 1$) might be affecting the system. This should be taken into account for the decision concerning fault F_j. The residual may also belong to *NZ* because of noise or modelling errors. To avoid this problem, it is possible to write rules, associated with each F_j, which use only the part of the signature which corresponds to 1 in the incidence matrix:

IF r_1 is *NZ* AND $D(1,j)$=1
AND r_M is *NZ* AND $D(M,j)$=1
THEN $Occ(F_j)$ is *True.*

The grade of membership of $Occ(F_j)$ is computed using equations (5) and (6):

$$\mu_{Occ(F_j)}(True) = \underset{i=1...M/D(i,j)=1}{\text{T-norm}}(\mu_{r_i}(NZ)) \qquad (5)$$

$$\mu_{Occ(F_j)}(False) = \underset{i=1...M/D(i,j)=1}{\text{T-conorm}}(\mu_{r_i}(Z)) \,. \qquad (6)$$

Equation (6) means that the *Occ* attribute of the fault F_j is *False*, if one of the residuals r_i belongs strongly to *Z* when $D(i,j)$ is equal to 1.

Example: Let $D(i=1...M,j) = [0\ 1\ 0\ 1]^T$ be the signature of the fault F_j, and the residual vector $C(k)=[r_1(k)\ \ r_2(k)\ \ r_3(k)\ \ r_4(k)]^T$. The membership of the fault *Occ* attribute to *True* is computed using the "min" or "max" operators as T-norm or T-conorm:

$$\mu_{Occ(F_j)}(True) = \min(\mu_{r_2}(NZ), \mu_{r_4}(NZ))$$
$$\mu_{Occ(F_j)}(False) = \max(\mu_{r_2}(Z), \mu_{r_4}(Z))$$

3.2.Simultaneity hypothesis rules.

The disjunction of two different signatures for multiple faults may lead to a signature which preserves all 1 of the respective single fault signatures. The simultaneity hypothesis is verified if at least one of the residuals r_i, $\forall\, i/D(i,j)=0$, is significantly affected and thus has a strong degree of membership to *NZ*. The computation processes the *Sim-hyp* fault attribute which describes fault F_j as represented in figure 3.

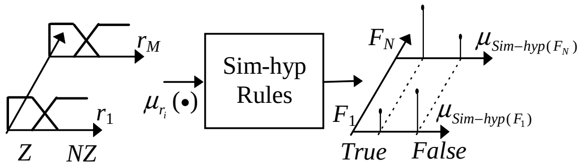

Fig. 3. Sim-hyp rules.

The membership of the simultaneity hypothesis attribute to *True* is defined by rules using only explicitly the residuals corresponding to 0 in the incidence matrix and testing if they are significantly affected:

IF r_1 is *NZ* AND $D(1,j)=0$ OR …
… OR r_M is *NZ* AND $D(M,j)=0$
THEN *Sim-hyp*(F_j) is *True*.

The grade of membership of the fault F_j *Sim-hyp* attribute to the term *True* is defined by the T-conorm:

$$\mu_{Sim\text{-}hyp(F_j)}(True) = \underset{i=1\ldots M/D(i,j)=0}{\text{T-conorm}} (\mu_{r_i}(NZ)) . \qquad (7)$$

On the other hand, if no residual $r_i/D(i,j)=0$ is affected, a combination with another fault is not possible. This fact makes it possible to generate a new rule translating the falseness of the simultaneity hypothesis:

IF r_1 is Z AND $D(1,j)=0$ AND …
... AND r_M is Z AND $D(M,j)=0$
THEN *Sim-hyp*(F_j) is *False*.

The membership degree of the fault F_j *Sim-hyp* attribute to the term *False* is defined by the T-norm:

$$\mu_{Sim-hyp(F_j)}(False) = \underset{i=1\ldots M/D(i,j)=0}{\text{T-norm}} (\mu_{r_i}(Z)) . \qquad (8)$$

3.3.Aggregation.

Through aggregation, the *Occ* and *Sim-hyp* attributes make it possible to determine if a fault F_j is a single fault or simultaneous with another fault. Two new attributes are defined: *Sim*(F_j) and *Sig*(F_j).

A fault F_j can be simultaneous with another fault if and only if fault F_j occurs and the simultaneity hypothesis is *True*. This is defined by the following rule:

IF *Occ*(F_j) is *True* AND *Sim-hyp*(F_j) is *True*
THEN *Sim*(F_j) is *True*.

The membership degree of the fault F_j *Sim* attribute to the term *True* is defined as an aggregation through the T-norm:

$$\mu_{Sim(F_j)}(True) = \text{T-norm} \qquad (9)$$
$$\{\ \mu_{Occ(F_j)}(True), \mu_{Sim\text{-hyp}(F_j)}(True)\ \}$$
$$\mu_{Sim(F_j)}(True) = \text{T-norm}$$
$$\{\ \underset{i=1\ldots M/D(i,j)=1}{\text{T-norm}} (\mu_{r_i}(NZ)), \underset{i=1\ldots M/D(i,j)=0}{\text{T-conorm}} (\mu_{r_i}(NZ))\ \}$$

A fault F_j is a single fault if it occurs and the simultaneity hypothesis is *False*. This is established by the rule:

IF *Occ*(F_j) is *True* AND *Sim-hyp*(F_j) is *False*
THEN *Sig*(F_j) is *True*.

The grade of membership of the fault F_j *Sig* attribute to the term *True* is defined by the T-norm:

$$\mu_{Sig(F_j)}(True) = \text{T-norm} \qquad (10)$$
$$\{\ \mu_{Occ(F_j)}(True), \mu_{Sim\text{-hyp}(F_j)}(False)\ \}$$
$$\mu_{Sig(F_j)}(True) = \text{T-norm}$$
$$\{\ \underset{i=1\ldots M/D(i,j)=1}{\text{T-norm}} (\mu_{r_i}(NZ)), \underset{i=1\ldots M/D(i,j)=0}{\text{T-norm}} (\mu_{r_i}(Z))\ \}$$

which is similar to the classical rule (2) taking into account all the elements of the signature vector $D(i,j)$, $i=1...M$.

Example: Let F_1 and F_2 be two faults; the residual vector is $C(k)^T=[r_1(k) \quad r_2(k) \quad r_3(k) \quad r_4(k)]$, and the incidence matrix is:

$$D(4\times 2) = \begin{bmatrix} 1 & 1 \\ 1 & 0 \\ 0 & 0 \\ 0 & 1 \end{bmatrix}.$$

The "min" (resp. "max") operator is used to compute a T-norm (resp. T-conorm):

$$\mu_{Occ(F_1)}(True) = \min(\mu_{r_1}(NZ), \mu_{r_2}(NZ))$$
$$\mu_{Sig(F_1)}(True) = \min(\mu_{r_1}(NZ), \mu_{r_2}(NZ), \mu_{r_3}(Z), \mu_{r_4}(Z))$$
$$\mu_{Sim(F_1)}(True)$$
$$= \min(\mu_{r_1}(NZ), \mu_{r_2}(NZ), \max(\mu_{r_3}(NZ), \mu_{r_4}(NZ)))$$
$$\mu_{Occ(F_2)}(True) = \min(\mu_{r_1}(NZ), \mu_{r_4}(NZ))$$
$$\mu_{Sig(F_2)}(True) = \min(\mu_{r_1}(NZ), \mu_{r_2}(Z), \mu_{r_3}(Z), \mu_{r_4}(NZ))$$
$$\mu_{Sim(F_2)}(True)$$
$$= \min(\mu_{r_1}(NZ), \mu_{r_4}(NZ), \max(\mu_{r_2}(NZ), \mu_{r_3}(NZ)))$$

For the single fault case (F_1):
$\mu_{r_1}(NZ)=1; \mu_{r_1}(Z)=0; \mu_{r_2}(NZ)=1; \mu_{r_2}(Z)=0;$
$\mu_{r_3}(NZ)=0; \mu_{r_3}(Z)=1; \mu_{r_4}(NZ)=0; \mu_{r_4}(Z)=1;$

and for the multiple fault case (F_1 and F_2):
$\mu_{r_1}(NZ)=1; \mu_{r_1}(Z)=0; \mu_{r_2}(NZ)=1; \mu_{r_2}(Z)=0;$
$\mu_{r_3}(NZ)=0; \mu_{r_3}(Z)=1; \mu_{r_4}(NZ)=1; \mu_{r_4}(Z)=0.$

Table 1 Attributes

	Single fault	multiple fault
$\mu_{Occ(F_1)}(True)$	1	1
$\mu_{Sig(F_1)}(True)$	1	0
$\mu_{Sim(F_1)}(True)$	0	1
$\mu_{Occ(F_2)}(True)$	0	1
$\mu_{Sig(F_2)}(True)$	0	0
$\mu_{Sim(F_2)}(True)$	0	1

The attribute computation results in table 1. The first column describes that fault F_1 is a single fault and fault F_2 has not occurred. The second column describes that fault F_1 occurs simultaneously with another fault, and fault F_2 occurs simultaneously with another fault.

3.4.Final decision.

The final decision must inform the operator about the faults affecting the system along with their membership degrees. The choice of a single fault affecting the system is made by searching for fault F_j which has the highest grade of membership of the *Sig* attribute to the term *True*. If this fault exists, it is chosen if its grade of membership of the *Sig* attribute to the term *True* is greater than or equal to the grade of membership of the *Sim* attribute to the term *True* of any other fault F_n (n=1...N with $n \neq j$). If no single fault is found, then all the faults F_n will be chosen so that their grade of membership of the *Sim* attribute to the term *True* are greater than the greatest grade of membership of the *Sig* attribute to the term *True* of all faults F_i (i=1...N).

The final decision is an N-column vector Fd:

$$\mu_{Sig(F_j)}(True) = \max_{n=1...N}(\mu_{Sig(F_n)}(True)) \tag{11}$$

$$\text{IF } \mu_{Sig(F_j)}(True) \geq \max_{n=1...N}(\mu_{Sim(F_j)}(True))$$

$$Fd = \left[0 \ \dots \ \mu_{Sig(F_j)}(True) \ \dots \ 0\right]$$

ELSE

$$Fd = \left[0 \ \dots \ \mu_{Sim(F_x)}(True) \ \dots \ \mu_{Sim(F_y)}(True) \ \dots \ 0\right]$$

$$\text{so that } \forall \text{ n}, \mu_{Sim(F_n)}(True) > \max_{i=1...N}(\mu_{Sig(F_i)}(True)).$$

4. APPLICATION TO AN AUTOMOTIVE ENGINE

4.1.Engine modelling.

An example is given to illustrate the multiple fault detection and isolation (MFDI) method developed above. The system considered is a 3.8L V6 automotive engine. Note that the diagnostic systems called OBD are of growing interest for automotive engineers because electronics play a preponderant role in injection and ignition strategies.

To achieve a compartmentalised model suitable for a diagnostic problem, the engine system has been divided into two sub-systems: the air intake system and the fuel supply system. For the sake of clarity the following example takes into account only the air intake system. Nevertheless, both sub-systems must be used to improve the performance of the MFDI.

Exact modelling of the air intake involves fluid mechanics. Details of the model and derivation of the equations can be found in (Bidan, et al., 1994). The behaviour of the process is modelled with non linear analytical equations such as incompressible air flow equations. A modified form of the discretised equations is presented below. Explicit residuals are functions of specific parameters that are not described for reasons of confidentiality.

Sensor variables are the throttle angle α, the manifold pressure *Pm*, the manifold temperature *Tm*, the ambient pressure *Pa* and the ambient temperature *Ta*. The air mass at the intake port is computed as a state variable. Residuals are computed as the difference between the data sensors and their model-based predictions. The incidence matrix (Table 2) is statistically isolable.

$r_1 = f(\alpha, P_m, T_a)$; $r_2 = f(\alpha, P_a)$;
$r_3 = f(P_m, T_m)$; $r_4 = f(P_m, P_a, T_a)$;
$r_5 = f(\alpha, T_m, T_a)$

Table 2 Incidence Matrix

	α	*Pm*	*Tm*	*Pa*	*Ta*
r_1	1	1	0	0	1
r_2	1	0	0	1	0
r_3	0	1	1	0	0
r_4	0	1	0	1	1
r_5	1	0	1	0	1

4.2.Results.

Two examples of faults are shown in this section. Many faults, such as leaks or sensor drifts, could affect the system. The faults introduced here correspond to sensor bias. This has been obtained by replacing the sensor connection to the central unit, by simulating a wrong sensor signal. In the first case (figure 5, left), bias has been applied to the throttle angle sensor and the manifold temperature sensor. In the second case (figure 5, right), erroneous manifold pressure and ambient temperature were substituted for the real ones.

Case a; bias over throttle and manifold temperature measurements were introduced. According to the incidence matrix (Table 1), both faults generate a new fault signature that corresponds to the logical OR between the α signature and the *Tm* signature, i.e. the first and the third column of the incidence matrix. This new signature is: $Sgn_a = [1\ 1\ 1\ 0\ 1]^T$.

Case b; in this example, a faulty manifold pressure sensor and ambient temperature sensor were considered. The new fault signature generated by these faults is: $Sgn_b = [1\ 0\ 1\ 1\ 1]^T$.

Diagnostic results are in Table 3 at time k = 2 s:

- In case a, the MFDI leads to the isolation of faults α and *Tm* with respectively 0.82 and 0.91 degrees of fault. These results are very satisfactory.

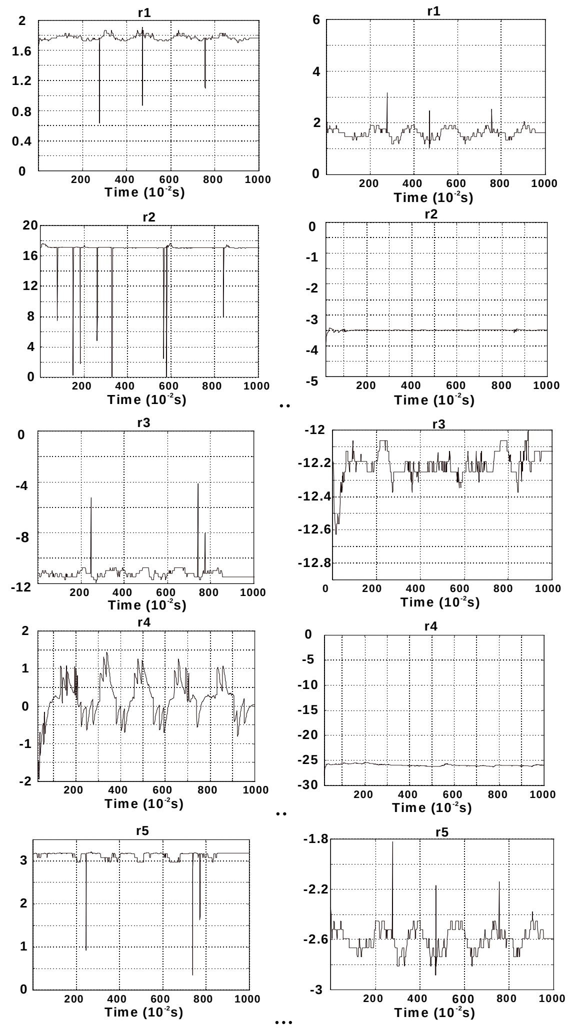

Fig. 4. Residuals with α (5%) and *Tm* (3%) faults in the first column; and residuals with *Pm* (10%) and *Ta* (10%) faults in the second column.

Table 3 Decision results

case a)	
Residual vector	$[1.73\ 17.48\ -11.3\ 0.93\ 3.13]^T$
Fuzzified residual vector for NZ	$[0.82\ 1\ 0.91\ 0.09\ 0.92]^T$
Fuzzified residual vector for Z	$[0.18\ 0\ 0.09\ 0.91\ 0.08]^T$
$\mu_{Sig(F_j)}(True)$	$[0.090\ \ 0\ \ 0\ \ 0.080\ \ 0]^T$
$\mu_{Sim(Fj)}(True)$	$[0.82\ \ 0.09\ 0.91\ \ 0.09\ \ 0.09]^T$
Fd	$[0.82\ \ 0\ \ 0.91\ \ 0\ \ 0]^T$

case b)	
Residual vector	$[2.41\ -3.5\ -12.18\ -26.8\ -2.21]^T$
Fuzzified residual vector for NZ	$[0.89\ \ 0.11\ \ 0.94\ \ 1\ \ 0.63]^T$
Fuzzified residual vector for Z	$[0.11\ \ 0.89\ \ 0.06\ \ 0\ \ 0.37]^T$
$\mu_{Sig(F_j)}(True)$	$[0\ \ 0.37\ \ 0\ \ 0.07\ \ 0.07]^T$
$\mu_{Sim(Fj)}(True)$	$[0.11\ \ 0.63\ \ 0.63\ \ 0.11\ \ 0.63]^T$
Fd	$[0\ \ 0.63\ \ 0.63\ \ 0\ \ 0.63]^T$

- In case b, the MFDI leads to the conclusion that faults *Pm*, *Tm*, *Ta* occur with a degree equal to 0.63 whereas only *Pm* and *Ta* measurements were effectively biased. If the faults over the manifold pressure and ambient temperature sensors are isolated, a false alarm involving the manifold temperature sensor is generated. This can be interpreted easily. The new fault signature generated by simultaneous faults "includes" another one. The logical OR between the first and the third fault signatures automatically causes a false alarm over the fourth fault signature. Such false alarms can be avoided by considering additional residuals: in this specific example, gathering all residuals from both sub-systems will considerably improve the isolation procedure.

5. CONCLUSION

A model-based fault detection and isolation has been described to support simultaneous faults. A qualitative reasoning based on fuzzy logic performs the decision procedure by aggregating the complementary information given by the 1 and the 0 of the incidence matrix. The properties of the incidence matrix structure has been used to reason about multiple fault without testing each combination. An implementation of this algorithm has been applied to an automotive engine.

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